STEADY-STATE AND DYNAMIC MYOELECTRIC SIGNAL COMPRESSION USING EMBEDDED ZERO-TREE WAVELETS

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ABSTRACT

Within the field on biomedical engineering, the majority of compression research has focused on encoding medical images, electrocardiograms, and electroencephalograms. Although long-term myoelectric signal (MES) acquisition is important for neuro-muscular system analysis and telemedicine applications, very few studies have been published on MES compression. This research investigates static and dynamic MES compression using the embedded zero-tree wavelet (EZW) compression algorithm and compares its performance to a standard wavelet compression technique.

INTRODUCTION

In a clinical environment myoelectric signals (MES) may be acquired for long periods of time and occupy a vast amount of storage. In addition, the transmission of these signals for telemedicine applications is time consuming for large quantities of data. Since data compression reduces the number of bits required to represent information, signals may be stored more efficiently, and lower bit-rates and reduced transmission time may be attained.

Within the field of biomedical engineering the majority of compression research has focused on encoding medical images, electrocardiograms, and electroencephalograms; however, very little literature can be found on compressing the MES. Norris *et al.* [1] and Chan *et al.* [2] investigated lossy compression of steady-state and transient MES using adaptive differential pulse code modulation (ADPCM), the *de facto* standard for voice compression. Guerrero *et al.* [3] compared the performance of common compression techniques, such as differential pulse code modulation, multi-pulse coding, and code excited linear prediction to transform-based compression techniques, when applied to intramuscular and the surface MES. Wellig *et al.* [4] investigated intramuscular MES compression using a modified version of Shapiro's [5] embedded zero-tree wavelet (EZW) compression algorithm.

This research investigates static and transient MES compression using the EZW compression algorithm and compares its performance to a standard wavelet compression technique. For the purpose of this investigation, the steady-state MES will be defined as the MES produced by an isometric isotonic, or static, contraction. Dynamic MES will be defined as the MES produced by an anisometric anisotonic, or dynamic, contraction.

DATA COMPRESSION

Data compression minimizes the number of bits required to represent information by reducing the redundancy present in the original signal. The reduction in storage requirement is usually expressed as a percentage using a figure of merit called the compression factor (CF).

$$\mathrm{CF}(\%) = \frac{U_S - C_S}{U_S} \mathrm{x}100 \qquad (1)$$

In (1) U_s is the original data size and C_s is the compressed data size. Lossless compression techniques attain low CFs and produce decompressed signals that are identical to the original data. Conversely, lossy compression techniques attain significantly higher CFs and produce decompressed signals that differ from the original signal. The reconstruction error is often expressed using a distortion metric called the percent residual difference (PRD).

$$\mathrm{PRD}(\%) = \sqrt{\frac{\sum_{i=1}^{N} \left(x_i - y_i\right)^2}{\sum_{i=1}^{N} x_i^{\,2}}}\,\mathrm{x}100 \qquad (2)$$

In (2) x is the original signal, y is the reconstructed signal, and N is the segment length.

TIME-FREQUENCY RESPRESENTATIONS

Conventionally, signals are transformed to their frequency representation using the Fourier Transform (FT); however, the FT is limited to the idea that frequency does not change with time. However, for signals with time-varying spectral characteristics it is

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Abstract

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necessary to accommodate the notion that frequency changes with time. Time-frequency representations (TFRs) represent signals in a domain that is a hybrid between time and frequency, and permit greater insight into the temporal variation of the signal's spectrum to be gained. The short-time Fourier Transform (STFT), although it provides both time and frequency localization, is constrained in that the time and frequency resolution in the time-frequency plane are constant. A fundamental characteristic of the WT is that within the time-frequency plane the time and frequency resolution can vary. At low frequencies the frequency resolution is good, and at high frequencies the time resolution is good. Therefore, for signals such as the MES that have a time-varying spectrum, the wavelet domain is often preferable to the Fourier domain.

METHODS

Four participants were recruited for this investigation. MES was acquired from the biceps brachii of the right arm at a sampling frequency of 2 kHz using a 12-bit analog-to-digital converter. For the steady-state MES acquisition, participants sustained a co-contraction of the bicep and tricep muscles for twenty seconds while data was acquired. For the dynamic MES acquisition, participants were seated with the upper-arm parallel to the torso, the elbow-joint angle at 90°, and a 5 lb. dumbbell in hand. Participants were instructed to cyclically contract and relax their bicep for twenty seconds at a frequency of 0.5 Hz (2 seconds/cycle). A single cycle is defined as a reduction in elbow-joint angle to approximately 40° followed by a return to the 90° starting position. The frequency was regulated using an electronic metronome comprised of a pulse generator driving a speaker.

The MES data were compressed using the EZW and standard wavelet compression algorithms, described below.

Embedded Zero-Tree Wavelet Compression

Two distinct properties of the EZW algorithm make it an effective means of compression. First, the EZW algorithm exploits the hierarchy of the wavelet transform (WT) coefficients, and establishes a connection between coefficients from different subbands. The WT coefficients are arranged such that every coefficient at a given scale, with the exception of those coefficients at the lowest scale, can be related to a pair of coefficients at the next finer scale. This is shown in Figure 1. Using this relationship, several coefficients can be encoded using a single symbol. Second, coefficients are encoded in order of importance using bit prioritization. The embedded coding scheme places the most important bits at the beginning of the bit-stream; therefore, the encoding or decoding process can terminate at any moment and allow a target bit-count or distortion metric to be met exactly. Since higher magnitude wavelet coefficients contribute more to the overall shape of the reconstructed signal, the EZW algorithm uses thresholding to extract larger coefficients from the hierarchy. The smaller coefficients are extracted by making multiple passes over the wavelet transform coefficients, decreasing the threshold by a factor of two with each pass.

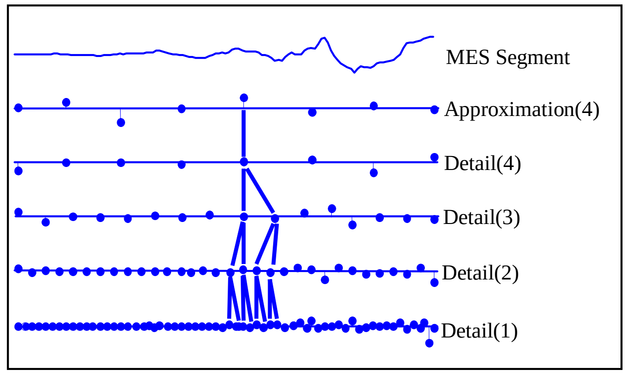

Figure 1: Tree-structure relationship between wavelet coefficients of different subbands. The bracketed numbers indicate the refinement level.

Standard Wavelet Compression

The standard wavelet compression algorithm, although significantly less complex than the EZW algorithm, cannot encode data to meet a target PRD. Data is encoded by zeroing WT coefficients until the desired CF is attained. Since lower magnitude coefficients contribute less to the overall shape of the signal, coefficients are zeroed in order of increasing magnitude, starting with the smallest.

RESULTS

The described algorithms were implemented in Matlab and tested on the steady-state and transient MES of four participants. The effects of data segment length and wavelet type on compression were empirically assessed. A trade-off analysis between EZW performance and complexity indicated segment lengths of 1024 samples were acceptable. The wavelet type analysis indicated no significant dependence of EZW performance on wavelet type. The steady-state and dynamic MES data were segmented into windows of 1024 samples and transformed to their time-frequency representation using the discrete Meyer wavelet in the WT. During the initial analysis, the decomposition depth was varied from 3 to 10 (the maximum depth for a 1024 sample segment). However, a comparison of the compressed signals across all depths indicated no dependence of compression performance on decomposition depth; therefore, to reduce computational time a level 5 decomposition was chosen.

The WT coefficients were compressed to CFs ranging from 60% to 95%. The PRDs between the original and decompressed signals were compared across algorithms. Figures 2 and 3 illustrate PRD variation with CF for the steady-state and dynamic MES.

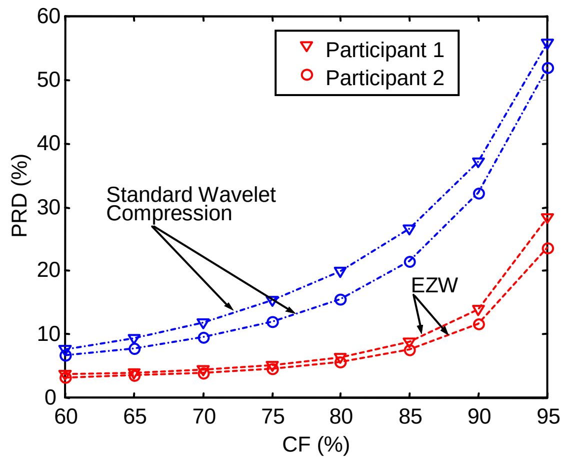

Figure 2: A comparison of EZW and standard wavelet compression performance when applied to the steady-state MES.

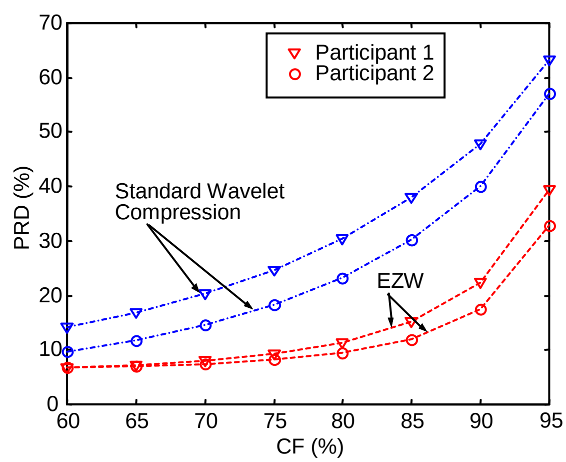

Figure 3: A comparison of EZW and standard wavelet compression performance when applied to the dynamic MES.

Results similar to those presented in Figures 2 and 3 were obtained for the other two participants.

To assess whether steady-state or dynamic MES data were more easily compressed, the PRD vs. CF curves for both types of MES were compared. The results of the EZW compression algorithm, when applied to the steady-state and dynamic MES obtained from the same subjects presented in Figures 2 and 3, are shown in Figure 4.

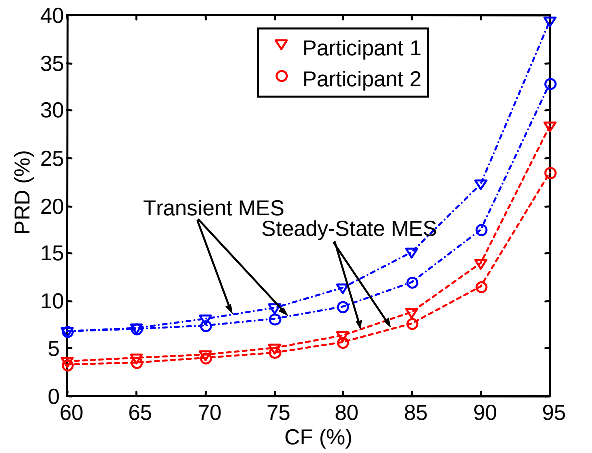

Figure 4: Comparison of steady-state and dynamic MES compression using EZW algorithm.

A comparison of computational complexity between the EZW and standard wavelet compression algorithms was also performed. Complexity was measured by counting the number of floating point operations (FLOPs) required to compress 20 seconds of MES. Figure 5 illustrates the variation of FLOP count with CF for the EZW and standard wavelet compression algorithms when applied to the steady-state MES of one subject.

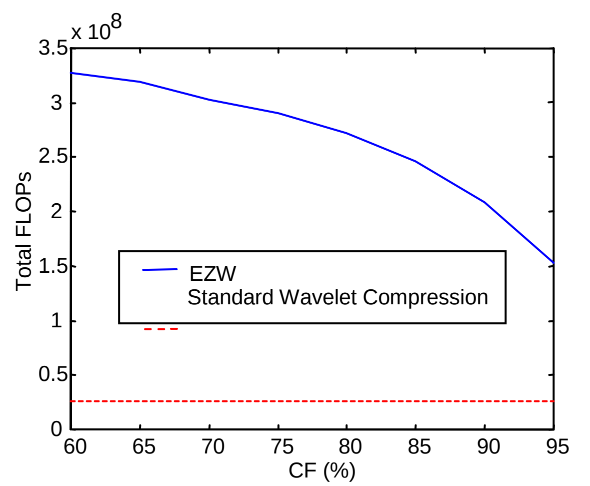

Figure 5: Computational complexity of EZW and standard wavelet compression algorithms when applied to 20 seconds of steady-state MES.

DISCUSSION

A comparison of the PRD vs. CF curves in Figures 2 and 3 shows that the EZW algorithm gives better results than the standard wavelet compression algorithm when applied to both the steady-state and dynamic MES data. For all CFs the EZW algorithm produced decompressed signals that, when compared to the original signals, gave PRD values that were substantially lower than those resulting from the standard wavelet compression algorithm. The main reason for this difference can be attributed to the nature of the EZW encoding. The EZW algorithm exploits the hierarchy of the WT coefficients and links coefficients from different subbands using a tree structure. This tree structure allows multiple coefficients to be encoded using a single symbol. When this encoding is coupled with bit prioritization, the most significant bits of the coefficients with the greatest magnitude are placed in the bit stream first. This method of encoding permits the storage or transmission of a larger quantity of information using fewer bits.

Although the comparison between the steady-state and dynamic MES presented in Figure 4 indicates steady-state MES compresses better than dynamic MES, this was not so for the other the other two participants. For all participants the steady-state MES compressed as well as, and sometimes better than, the dynamic MES. It was originally hypothesized that the dynamic MES would compress more efficiently than the steady-state MES due to the higher degree of redundancy present in the dynamic MES generated by a cyclic contraction. Since improved compression performance of the dynamic MES over the steady-state MES was not observed, it is speculated that compression may be more subject dependant than MES type dependant.

The comparison of the computational complexity for the two compression algorithms shown in Figure 5, clearly indicates that EZW encoding is computationally expensive, regardless of the CF. The decreasing FLOP count with increasing CF is the result of reduced data processing associated with higher degrees of compression.

CONCLUSION

This research investigated MES compression using the EZW encoding algorithm, and compared its performance to a standard wavelet compression algorithm. The results clearly indicate a trade-off between computational complexity and decompressed signal distortion. Although the EZW algorithm compresses the MES with considerably less loss than the standard wavelet compression algorithm, it is computationally more expensive in terms of FLOPs. It is surmised that the compressibility of steady-state and dynamic MES data is more subject dependant than MES type dependant, since no relationship between compression performance and MES type could be established.

The results of this investigation indicate the choice of an appropriate MES compression algorithm is highly dependent on the application. However, if a target distortion metric is to be used as the stopping criteria for encoding or decoding, the EZW algorithm is the suitable choice, as this property is not easily implemented with other compression algorithms.

REFERENCES

[1] **Norris, J.F. and D.F. Lovely**, "Real-time compression of myoelectric data utilizing adaptive differential pulse code modulation", *Med. Biol. Eng. Comput.*, 33, pp. 629-635, 1995.

[2] **Chan, A.D.C., Lovely, D.F. and B. Hudgins**, "Errors associated with the use of adaptive differential pulse code modulation in the compression of isometric and dynamic myoelectric signals", *Med. Biol. Eng. Comput.*, 36, pp. 215-219, 1998.

[3] **Guerrero, A.P. and C. Mailhes**, "On the Choice of an Electromyogram Data Compression Method", *Proceedings of the 19th International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 1558-1561, 1997.

[4] **Wellig, P., Cheng, Z., Semling, M. and G.S. Moschytz**, "Electromyogram Data Compression Using Single-Tree and Modified Zero-Tree Wavelet Encoding", *Proceedings of the 20th International Conference of the IEEE Engineering in Medicine and Biology Society*, 20(3), pp. 1303-1306, 1998.

[5] **Shapiro, J.M.**, "Embedded Image Coding Using Zerotrees of Wavelet Coefficients", *IEEE Trans. on Signal Processing*, 41(12), pp. 3445-3462, December 1993.

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